

1 **Title:** Toward measuring biogeochemistry within the stream-groundwater interface at the
2 network scale: an initial assessment of two spatial sampling strategies

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6 **Running Head:** Network scale stream-groundwater biogeochemistry

7 **Keywords:** surface water-groundwater, watershed, dissolved organic carbon, nitrogen, stream,
8 biogeochemistry, scale

9

10 **Abstract**

11 It is important to understand how point measurements across spatially heterogeneous
12 ecosystems are scaled to represent the system of interest. Stream biogeochemistry presents an
13 illustrative example because water quality concerns within stream networks and recipient water
14 bodies motivate heterogeneous watershed studies. Measurements of the stream water-
15 groundwater (SW-GW) interface (i.e., the shallow subsurface of streams) are well-documented
16 for small, point-scale sampling density measurements (i.e., $\text{cm}^2\text{-m}^2$ features), but poorly
17 characterized for larger, watershed-scale sampling density measurements (i.e., km^2 ; stream
18 reaches and networks). Further, sampling the SW-GW interface is more time- and labor-
19 intensive than surface water sampling, meaning sample point selection must be made with care
20 when attempting a network-scale analysis. In this study, we endeavor to determine which of two
21 common spatial sampling schemes is appropriate for characterizing the biogeochemistry of the
22 SW-GW interface across a temperate, third-order stream network, focusing on dissolved organic
23 carbon. The first scheme, called here Local Sampling, focuses on characterization of the small-
24 scale ($< 10 \text{ m}^2$) variability produced by the local physical and biogeochemical heterogeneity,
25 with fewer points across the stream network. The second scheme, called here Longitudinal
26 Sampling, has approximately the same number of measurements distributed over many more
27 points across the stream network with less characterization of local variability. This comparison
28 reveals that selection of a Local Sampling versus a Longitudinal Sampling scheme influences the
29 interpretation of biogeochemical patterns at the stream network scale. Additionally, this study
30 found an increase in observation efforts at the local scale added limited information for reach- to
31 network-scale biogeochemical patterns, suggesting that emphasis should be placed on
32 characterizing variability across broader spatial scales with the Longitudinal Sampling approach.

33 **Introduction**

34 At what spatial resolution do we make measurements and observations to characterize
35 patterns and processes across stream networks? It is well-established in terrestrial landscape
36 ecology that measurements made at a certain spatial sampling density (i.e., resolution or grain
37 size) can be extrapolated to different scales of spatial extent (e.g., Schneider 1998; Wu and Li
38 2006). However, the best practices for extrapolating between scales are continually evolving,
39 including many methods that have been developed to upscale or downscale observations to
40 different resolutions (Turner and Gardner 2015). Few studies have presented best sampling
41 practices and methods across scales for aquatic ecosystems. Streams and their interfaces with
42 groundwater are particularly challenging for choosing the most appropriate sampling resolution
43 due to the inherent effects of directionality in flowing water and logistical challenges of
44 measuring surface water and groundwater parameters. To determine the ecological conditions
45 and functioning of the stream water-groundwater (SW-GW) interface that are relevant to
46 landscape biogeochemical budgets, watershed management, and ecosystem theories at the reach
47 to network scales (Krause et al. 2011; Bernhardt et al. 2017), we must address how best to
48 measure SW-GW interactions across spatial and temporal scales.

49 At stream network scales, the River Continuum Concept (RCC; Vannote et al. 1980) was a
50 key step in starting to address the landscape ecology of stream networks, including the effects of
51 directional flow through streams. The RCC postulated a gradient, moving from headwaters to
52 higher-order streams, to explain the downstream movement and transformation of organic matter
53 by physical and biological processes. Although aspects of the RCC are still debated (see, e.g.,
54 Creed et al. 2015; Rosi-Marshall et al. 2016), the general conceptual model of a gradient wherein
55 the biogeochemistry of stream reaches changes systematically from upstream to downstream in

56 networks is central to contemporary literature of stream ecosystems (e.g., Poole 2002; Thorp and
57 Bowes 2017). The RCC is raised here not to debate its strengths and weaknesses in explaining
58 how conditions may change through a river network, but because it did not specify what scale of
59 measurements is needed to assess the ecological hypotheses of the RCC. Hence, there is still
60 uncertainty in how to assess the RCC. However, in a review of stream ecology and
61 biogeochemistry, Fisher et al. (2004) identified a broad understanding that streams are largely
62 influenced by longitudinal (i.e., upstream/downstream) changes, and are composed of a
63 multitude of parallel flowpaths leading to a high degree of heterogeneity. Other studies have
64 stressed that nearby sampling points of stream chemistry were very similar, but were able to
65 maintain a broader heterogeneous trend (Dent and Grimm 1999).

66 Generally, spatial biogeochemical variation in surface waters decreases with increasing
67 stream order (Temnerud and Bishop 2005), but there is evidence in some streams that
68 comparable variability can be found at all scales depending on the sampling density (Zimmer et
69 al. 2013; Abbott et al. 2018). This spatial biogeochemical variability suggests that the role of
70 study design, especially the spatial resolution of sampling, can introduce bias or confusion in our
71 understanding of stream ecology. Furthermore, the biogeochemical variability in SW-GW
72 interfaces across stream networks is virtually unknown and almost never documented in the
73 literature (but see Ruhala et al. 2018). This is particularly true for assessing the structure and
74 dynamics of the hyporheic zone (HZ), the ecotone where stream water readily interacts and
75 exchanges properties with groundwater (Boulton et al. 1998). The HZ is a known
76 biogeochemical control point in watersheds influencing ecosystems and water quality (McClain
77 et al. 2003; Bernhardt et al. 2017). The primary limitation with sampling sediment pore water in
78 the SW-GW interface is that it can be time- and labor-intensive, given that porewater must be

79 drawn out slowly to avoid disrupting stream, hyporheic, and groundwater flow fields (i.e.,
80 typically $< 5 \text{ ml min}^{-1}$) (e.g., Duff et al. 1998). The SW-GW interface is also known to exhibit
81 large spatiotemporal heterogeneity in physical and biological conditions (Boano et al. 2010).

82 Our understanding of SW-GW interface biogeochemistry at stream network scales has been
83 limited by a lack of understanding of how to best allocate sampling efforts in space and time.
84 The local scale (i.e., the within-reach scale) over which SW-GW interface data are typically
85 collected does not match the stream network scale at which many environmental problems need
86 to be addressed (Krause et al. 2011). In fact, most SW-GW interface studies do not make direct
87 measurements in the SW-GW interface, and instead use indirect measurements (i.e., tracer
88 studies) that span a longitudinal scale of 10-1000 m (Ward 2016). These indirect measurements
89 are often rife with model uncertainty and interpretation, especially for quantifying SW-GW
90 exchange (Kelleher et al. 2013). Despite the lack of direct measurements, significant advances in
91 process-based modeling of SW-GW processes at the stream network scale have proceeded,
92 including the transport and fate of nutrients (Kiel and Cardenas 2014; Gomez-Velez et al. 2015).
93 Unfortunately, there is still a paucity of data sets of the SW-GW interface at the network scale
94 available to validate these types of models.

95 In thinking about a sampling scheme of the SW-GW interface across an entire stream
96 network, one must consider the effort spent for an individual sampling point while ensuring that
97 the limited available number of sampling points reasonably represent the entire network.
98 Generally, there are two stream network-scale sampling schemes that appear in the literature
99 (Figure 1): 1) high-resolution characterization of local-scale variability at few sites across the
100 network (e.g., Zimmer et al. 2013; hereafter Local Sampling), wherein effort is focused on taking
101 many samples at specific local-scale features in a watershed instead of fewer samples at more

102 locations, or 2) low-resolution characterization of local-scale variability at many sites across the
103 network, (e.g., McGuire et al. 2014; hereafter Longitudinal Sampling), wherein effort is focused
104 on taking samples at more locations across the entire network instead of more samples at specific
105 local-scale features. The schemes are either deliberately or arbitrarily selected to investigate
106 properties relevant to stream network biogeochemistry. Local Sampling is often applied for
107 investigations of specific SW-GW processes, while there are very few examples of Longitudinal
108 Sampling studies for any type of SW-GW processes (Ward 2016). However, it is unknown
109 whether one of these two sampling schemes is more appropriate for research questions dealing
110 with characterization of SW-GW interface biogeochemistry at the network-scale. Our objectives
111 in this paper are to raise awareness regarding SW-GW sampling design unknowns and to begin
112 addressing these unknowns in our investigation of network-scale SW-GW interactions by
113 comparing the two common sampling schemes across a stream network. Determining which
114 scheme, Local Sampling or Longitudinal Sampling, best characterizes the overall stream network
115 to will help advance SW-GW investigations and thus guide best sampling practices (Krause et al.
116 2011). To direct these main objectives, we developed the following hypotheses:

117 H1: A single point profile is representative of multiple point profile measurements of SW-
118 GW interface biogeochemistry, because inter-reach variability will be greater than intra-reach
119 variability. This hypothesis will assess whether sampling of the SW-GW interface should focus
120 on fewer points at more sites in a network or if it is necessary to have many points to
121 characterize each individual site, which, in turn, will guide sampling design for future SW-GW
122 studies.

123 H2: Variance in SW-GW interface biogeochemistry profiles will decrease with increasing
124 stream order, because the effects of upstream processes are integrated downstream due to

125 directional flow. This hypothesis will help inform the development of network continuum
126 concept in the SW-GW interface, such as the continuum concepts of the RCC.

127 To evaluate these objectives and hypotheses, we analyzed a spatially intensive sampling of
128 SW-GW biogeochemistry (as compared to other SW-GW interface studies in the literature) in a
129 stream network that spans the two study sampling schemes (Ruhala et al. 2018). Specifically, we
130 focus on the surface water and SW-GW interface pore-water concentrations of dissolved organic
131 carbon (DOC) in a lowland, third-order, mixed land use watershed. DOC was selected as the
132 focus for this initial assessment because it is a fundamental control on water quality and
133 ecosystem ecology of freshwaters due, in part, to its role in nutrient and metal cycling, ability to
134 influence pH, effect on net carbon balances, and control of photochemistry (Aiken 2014). In
135 addition to DOC, we include analyses for select anions, including chloride (Cl^-) and nitrate (NO_3^-
136) to represent nonreactive and reactive solutes, respectively (e.g., Triska et al. 1993; Barber et al.
137 2005; Zarnetske et al. 2011; Bernhardt et al. 2017).

138

139 **Materials and Procedures**

140 *Site description* – The data sets used in this study were generated by Ruhala et al. (2018) in
141 Augusta Creek (Figure 2), which is a low gradient, third-order watershed draining 98 km² in
142 southwest Michigan, USA. The watershed is composed of glacial till, and flows through a
143 mixed-use landscape that includes wetlands, lakes, agriculture, and upland forests. The stream is
144 primarily groundwater-fed, gaining water along much of its length, and the low overland runoff
145 as well as abundant wetlands and lakes along its course buffer the stream discharge response to
146 storm events (Poff et al. 1997; Hamilton et al. 2018). Stream reaches included in this study range
147 from first- to third-order, with variable origins including lake outflows, wetland outflows, and

148 forested headwater streams (Figure 2). Located near the W.K. Kellogg Biological Station of
149 Michigan State University (KBS), Augusta Creek is a historically important site for freshwater
150 biogeochemical and ecological research. For example, it was a site in the seminal RCC and
151 Natural Flow Regime papers (Vannote et al. 1980; Poff et al. 1997), is part of the KBS Long
152 Term Ecological Research site activities, and has an active, long-term (>50y) United States
153 Geological Survey (USGS) gaging station (04105700).

154

155 *Sampling schemes*: Ruhala et al. (2018) collected data that span the Local Sampling and
156 Longitudinal Sampling schemes, and importantly, each sampling date represented roughly the
157 same field sampling effort (~10 field work days for 4 researchers), the same sampling techniques
158 and equipment, and a comparable total number of SW-GW biogeochemical sample locations
159 ($n \approx 40$). However, the team distributed these sampling points differently across the stream
160 network, stratifying the sampling to capture most subwatersheds and all stream orders in the
161 Augusta Creek watershed. The sampling scheme roughly corresponded to the two study scheme
162 types, Local and Longitudinal (Figure 2).

163 In the data set, Local Sampling samplings characterized the local heterogeneity of a
164 limited number of sites across the network and were carried out from 10-17 August 2015. In the
165 Local Sampling scheme, 16 locations, stratified by stream order (first through third) were
166 selected across the network (Figure 2). Within each location, 3 MINIPOINT porewater
167 piezometers (Duff et al. 1998) were deployed close to each other (<3 meters apart), and hereafter
168 the group of three samplers will be referred to as a plot (Figure 1). The MINIPOINT porewater
169 piezometers are relatively non-invasive and allow sampling of pore water profiles from six
170 discrete depths in the SW-GW interface (Duff et al. 1998), set between 2.5 and 20 cm as detailed

171 in the next section and Ruhala et al. (2018). Thus, there were 18 SW-GW samples collected at
172 each of the 16 plots for a total of 288 unique SW-GW biogeochemical sample locations from the
173 Local Sampling approach. In Augusta Creek, most of the stream sediment is unconsolidated
174 sandy and gravelly sediments, which is compatible with the MINIPOINT technology. However,
175 the exact MINIPOINT porewater piezometer location at a selected site depended on the capacity
176 to physically insert all the piezometers the specified depth into the sediment (i.e., sites with
177 cobble or armored sediments could not be sampled).

178 The Longitudinal Sampling scheme represented a coarser characterization of local
179 heterogeneity, but increased the total number of plots across the stream network and thus was
180 meant to capture the spatial variability across the stream network. This sampling was carried out
181 from 16-22 August 2016 during similar seasonal, stream DOC conditions, and daily discharge
182 conditions as the Local Sampling campaign (Figure 3), though 2016 data was collected during
183 discharge recession from a preceding high flow event. For Longitudinal Sampling, a similar field
184 effort yielded 39 points across the network. At each location, a single MINIPOINT porewater
185 piezometer was sampled, optimally collecting six porewater samples per point for a total of 230
186 unique SW-GW biogeochemical sampling locations from the Longitudinal Sampling.

187 Furthermore, given that we are specifically interested in the biogeochemistry with respect
188 to DOC at larger spatial scales, we also analyzed data grouped by stream order similar to the
189 RCC (Vannote et al. 1980). Stream order acts as a proxy for the physical hydrography of stream
190 reaches, which in turn is fundamental to ecological patterns and processes (Harvey and Gooseff
191 2015). It is a simple method to discretize the network that allows for quick analysis of how an
192 ecological variable related to DOC varies from upstream to downstream through a stream
193 network (e.g., Creed et al. 2015). In the Local Sampling scheme there were 6 first-order, 5

194 second-order, and 5 third-order locations, while the Longitudinal Sampling scheme was
195 composed of 16 first-order, 14 second-order, and 9 third-order plots. This enables an assessment
196 of how the biogeochemistry changes with different hydrological characteristics distributed from
197 headwaters to mainstem outlet (as addressed by H2 above).

198

199 *Sample and data collection* – To illustrate the procedure and effort involved in collecting SW-
200 GW samples, here we briefly review the sampling protocol from Ruhala et al. (2018). Each
201 MINIPOINT porewater piezometer was deployed to collect six discrete samples at 2.5, 5, 7.5,
202 10, 15, and 20 cm depth. The MINIPOINTS were attached to a Masterflex peristaltic pump
203 (Cole-Parmer) using L/S Tygon tubing, and water was drawn from the SW-GW at a rate of 2.5
204 ml min⁻¹. They collected 80 mL of water from each depth. They used 20 mL of sample as a rinse
205 through the filter (Whatman GF/F, 0.7 µm nominal pore size) to remove particulate matter. The
206 remaining 60 mL was filtered through the 0.7 µm filter to remove particulates and larger
207 microbes the placed in acid-rinsed HDPE amber bottles and stored on ice. At the end of the
208 sampling day, 10 mL were first used to rinse through a filter (Sartorius Stedim cellulose acetate,
209 0.2 µm nominal pore size), then the remaining 50 mL were filtered and stored in the dark at 4°C
210 and analyzed within 28 days. Each filtered sample was analyzed for non-purgeable organic
211 carbon using a TOC-L total organic carbon analyzer (Shimadzu) with Pt-catalyzed oxidation at
212 680°C. Concentrations for Cl⁻ and NO₃⁻ were analyzed on a Dionex ICS-2100 Ion
213 Chromatography System (ThermoScientific).

214

215 *Data analysis* – The Local Sampling data were divided into points, representing a single
216 MINIPOINT with six samples at vertically distributed depths, and plots representing three

217 MINIPOINTS with eighteen samples, varying in depth, at a single site (Figure 4). The
218 Longitudinal Sampling data was simply divided into points, as there was only a single
219 MINIPOINT with six vertically distributed samples deployed at each individual site. We
220 calculated variance for a point as the variance across the six individual depths from a
221 MINIPOINT sampling, and variance for a plot as variance across all eighteen samples (6 depths
222 at 3 points) from the clustered MINIPOINTS (Figure 5) as:

$$223 \sigma^2 = \sum \frac{(X-\mu)^2}{N} \quad (1)$$

224 where X is a biogeochemical concentration value at one discrete piezometer (within a
225 MINIPOINT array for point variance and within the three MINIPOINT arrays for plot variance),
226 μ is the mean of all concentration measurements (again, within a single MINIPOINT array for
227 point variance and for all three MINIPOINT arrays for plot variance), and N is the number of
228 observations ($N=6$ for point variance, $N=18$ for plot variance).

229 For the Local Sampling data, to assess the relative utility of a single MINIPOINT as
230 compared to three MINIPOINTS we took the ratio of the plot variance to point variance (F),
231 shown as:

$$232 F = \frac{\sigma^2_{\text{plot}}}{\sigma^2_{\text{point}}} \quad (2)$$

233 where σ^2 is the variance (Equation 1) and the subscripts represent the plot and points. Finally, to
234 compare the full distributions of point and plot measurements across stream orders we used a
235 non-parametric Wilcoxon Rank Sum Test (Wilcoxon 1945) implemented in the software R v
236 3.4.2 (R Core Team 2017). The Wilcoxon Rank Sum Test allows us to assess whether the
237 distribution of samples within orders are increasing or decreasing across first, second, and third
238 orders. This assessment is used to determine if similar patterns emerge when comparing point
239 and plot measurements and when comparing Local Sampling to Longitudinal Sampling.

240

241 **Assessment**

242 Concentrations of DOC in the SW-GW interface were comparable between the Local
243 Sampling and Longitudinal Sampling schemes across the network and across samplings grouped
244 by stream order (Figure 6). Minimum and maximum SW-GW DOC concentration values for the
245 Local Sampling were 1.50 and 15.70 mg L⁻¹, respectively, while minimum and maximum SW-
246 GW DOC concentration values for the Longitudinal Sampling were 1.34 and 17.04 mg L⁻¹,
247 respectively (Figure 6).

248

249 *Local Sampling scheme results* – Point measurements of DOC exhibited a general decrease in
250 variance from first- to third-order (Figure 7a), where there are significant differences among
251 first- to third-order variances ($p < 0.05$). Plot measurements of DOC also exhibited decreasing
252 variance from first- to third-order (Figure 7b) with significant differences noted ($p < 0.05$). The
253 DOC variance ratio, F from equation 2, ranged from 0.4 to 4.3, 0.5 to 2.3, and 0.4 to 2.4 for first-
254 , second-, and third-order streams, respectively (Figure 8a). The corresponding median ratio
255 values for first-, second-, and third-order streams were 1.2, 1.0, and 1.2, respectively.

256 Variance of NO₃⁻ point measurements appeared to decrease from first- to second-order
257 and then increase from second- to third-order (Figure 7d), and were significantly different across
258 orders ($p < 0.05$). Plot-scale variance of NO₃⁻ indicates a decrease from first- to second-order
259 and a decrease from second- to third-order (Figure 7e), with first- through third-order exhibiting
260 significant differences ($p < 0.5$). The NO₃⁻ variance ratio ranged from 0.4 to 40.1, 0.5 to 5.9, and
261 0.4 to 70.9 for first-, second-, and third-order streams, respectively (Figure 8b). The

262 corresponding median values for first-, second-, and third-order streams were 1.3, 1.0, and 1.1,
263 respectively.

264 Point measurements of Cl^- increased from first- to third-order (Figure 7g) and were
265 significantly different ($p < 0.05$). Variances of plot measurements of Cl^- were not significantly
266 different from first- to third-order streams (Figure 7h, $p = 0.35$). The Cl^- variance ratio ranged
267 from 0.5 to 22.6, 0.5 to 14.7, and 0.6 to 2.4 for first-, second-, and third-order streams,
268 respectively (Figure 8c). The corresponding median values for Cl^- in first-, second-, and third-
269 order streams were respectively 1.0, 0.8, and 1.0.

270

271 *Longitudinal Sampling scheme results* – The plot variances of DOC had an apparent increase
272 from first- to third-order streams (Figure 7c) and were significantly different among orders ($p <$
273 0.05). Plot variances of NO_3^- decreased from first- to third-order (Figure 7f) and were
274 significantly different ($p < 0.05$). The plot variances of Cl^- decreased from first- to second-order
275 (Figure 7i) and were significantly different ($p < 0.05$), but a post-hoc Dunn test (Dunn 1964)
276 indicated that there was no significant difference between second- and third-order plot variances
277 ($p = 0.09$).

278

279 **Discussion**

280 Our analysis of spatial heterogeneity of porewater chemistry from samples throughout the
281 Augusta Creek network reveals several critical insights into how to best collect spatial data from
282 the SW-GW interface at the network-scale. Further, this analysis helps demonstrate that SW-GW
283 investigators must be cognizant of how to sample when interested in larger spatial patterns,

284 especially when considering how stream networks remove or transform reactive biogeochemical
285 solutes.

286

287 *Guiding future sampling* - The results offer an indication of how to best invest our future
288 sampling efforts when a network-scale assessment of SW-GW interface biogeochemistry is the
289 goal. Primarily, in Augusta Creek, we find that there is little added value in increasing
290 characterization of the local, plot-scale spatial heterogeneity, particularly for the reactive
291 biogeochemical components DOC and NO_3^- . The point:plot ratio in the Local Sampling scheme
292 generally centered on a value of 1 (Figure 8) for reactive (DOC and NO_3^-) and nonreactive
293 solutes (Cl^-), meaning that a single sampling array at a site can approximate the variance of a site
294 as well as three separate sampling arrays at a site. In fact, new patterns of variability emerge
295 when focusing on sampling across the stream network as opposed to more detailed local
296 characterization (e.g., Figures 7a and 7b to 7c and Figures 7d and 7e to 7f for DOC and NO_3^- ,
297 respectively), wherein the patterns of variance moving from headwaters to downstream locations
298 actually changes when enacting a Longitudinal Sampling scheme as compared to a Local
299 Sampling scheme.

300 These results indicate that a Longitudinal Sampling scheme may be preferable to a Local
301 Sampling scheme when investigating the biogeochemistry of the SW-GW interface at the
302 network-scale. This finding is corroborated by two recent papers that present conceptual and
303 reduced complexity models to understand DOC (Hotchkiss et al. 2018) and NO_3^- (Marzadri et al.
304 2017) processing as they move from headwater to downstream locations (i.e., from low to high
305 order streams), including the potential differential effects of the SW-GW interface across the
306 river network. Our assessment of the two main spatial sampling schemes for SW-GW interface

307 and the specific results from Augusta Creek inform how future researchers can attempt to
308 evaluate and validate these new conceptual and modeling frameworks as well as historically
309 important frameworks such as the RCC (Vannote et al. 1980).

310 The variance ratios observed between the two sampling strategies suggest that point
311 measurements are reasonably representative of plot measurements in Augusta Creek, because
312 median values for all ratios are generally equal to unity (i.e., the ratio of the variance within a
313 plot is close to the variance of each individual point). A Wilcoxon Rank Sum Test of the
314 distributions of variance ratios indicates that point and plot (mean of three points) measurements
315 are similar for most chemistry samples, with the exception of DOC and NO_3^- in third-order
316 reaches. However, the median values of plot to point ratios in third-order streams are still
317 relatively close to unity (1.23 for DOC, 0.99 for Cl^- , and 1.12 for NO_3^-). Therefore, for this
318 stream network under summer baseflow conditions, the results suggest that the SW-GW
319 interface biogeochemistry of first- and second-order streams can be characterized with less focus
320 on the local intra-site heterogeneity, which allows more focus on the inter-reach heterogeneity.
321 In other words, more valuable data about network-scale SW-GW biogeochemical conditions can
322 be collected using the Longitudinal Sampling scheme as compared to the Local Sampling
323 scheme.

324 The observed reduction in variances of porewater concentrations moving downstream
325 was dependent upon the biogeochemical species of interest. In the Local Sampling campaign,
326 DOC variance at different sampling densities generally decreased moving from first- to third-
327 order streams (Figure 7a and b). Conversely, Cl^- variance in Local Sampling increased from first-
328 to third-order streams for both sampling densities (Figure 7g and h). NO_3^- variance exhibited an
329 inconsistent trend in Local Sampling, wherein it increased from first- to second-order, then

330 decreased from second- to third-order (Figure 7d and e). In Longitudinal Sampling the NO_3^-
331 variance generally decreased with increasing stream-order (Figure 7c). The reduction in DOC
332 variance with increasing stream order reflects the accumulation and mixing of all upstream
333 inputs (Abbott et al. 2018). Synthesis studies of DOC across stream networks indicate that,
334 indeed, the variability of DOC typically decreases with an increase in disconnection from
335 terrestrial sources (e.g., Creed et al. 2015).

336 Most stream networks have the majority of total stream length in first- and second-order
337 streams (e.g., first-order = 52% and second-order = 25%, Downing et al. 2012), so the finding
338 that the low-order streams in Augusta Creek can be characterized with less focus on intra-site
339 heterogeneity means that more low-order locations should be sampled (i.e., the Longitudinal
340 Sampling scheme), rather than investing efforts in plot replication at each location. Historically,
341 SW-GW interface research has disproportionately focused on second-, third-, and fourth-order
342 streams (Ward 2016), so more effort should be directed to first and >fifth-order stream SW-GW
343 interfaces in networks if we are to better represent SW-GW conditions in future network scale
344 biogeochemical studies and models. Headwaters are demonstrably important in terms of the
345 contribution of biogeochemical processes to downstream nutrient export (Alexander et al. 2007;
346 Boano et al. 2014). Further, smaller networks tend to display the highest variability in water
347 quality (Wolock et al. 1997; Temnerud and Bishop 2005; Abbott et al. 2018).

348
349 *Different sampling resolution concerns* - The Longitudinal Sampling campaign, with low local
350 characterization in favor of higher longitudinal spatial resolution across the stream network, can
351 potentially result in an entirely different interpretation of SW-GW conditions and DOC stream
352 processing. DOC and Cl^- trends across orders were the opposite as compared to the trends

353 observed in the Local Sampling scheme. Here, DOC variance is generally increasing, while Cl^- is
354 generally decreasing moving from upstream to downstream (Figure 7c, f). While Cl^- fits our
355 hypothesis (H2), DOC does not support it. This is an important revelation given that the same
356 stream system was sampled under similar weather and hydrologic conditions (albeit in a different
357 year), but changing the spatial SW-GW sampling scheme yielded a completely different apparent
358 pattern across the network. These fundamental differences moving from headwaters to
359 downstream locations have raised concerns particularly for empirical and mechanistic modeling.
360 If data input into a model has a different pattern of variance depending on the sampling scheme,
361 then the results of those models and conclusions that can be drawn from them will be entirely
362 different from one scheme to the next.

363 Though studies comparing biogeochemistry at different scales are generally absent from the
364 literature for the SW-GW interface, several researchers have identified the importance of scale in
365 studies of SW-GW interface processes. The concerns of how sampling resolution will impact
366 attempts to interpret or model the biogeochemical function of SW-GW interactions is more
367 important than ever now that data users, including modelers, managers, and decision makers, are
368 often thinking at river network scales (Krause et al., 2011). This will lead to an increase in
369 demand for river network scale SW-GW biogeochemical data, and those seeking to collect that
370 data must grapple with sampling effort and how resolution of sampling can impact the various
371 data users. While SW-GW biogeochemical investigations at the network scale are limited, there
372 are complementary ecological studies that offer further guidance. Ecological researchers have
373 long known that different processes are scale-dependent and the scale at which one measures
374 should answer the question being asked (e.g., Allen and Starr 1982; Delcourt et al. 1982). River
375 corridor investigators addressing different research questions have observed spatial-resolution

376 and extent dependent patterns, for example, small-scale biotic diversity as compared to larger-
377 scale diversity in the SW-GW interface (see review paper by Vinson and Hawkins 1998) or
378 comparing the riparian subsurface flow paths in small vs. large scales (see Dahl et al. 2007).
379 Because it is important to understand all ecological processes at a variety of scales, the present
380 study endeavored to assess how to best measure at an unprecedented network-scale in the SW-
381 GW interface. This study helps raise some potential concerns about sampling schemes and their
382 impact on understanding the SW-GW interface across spatial scales, and therefore should help
383 guide future research interested in collecting and using data to compare processes across spatial
384 scales. It also underscores that researchers cannot ignore that they must carefully consider what
385 spatial sampling scheme may be best for the SW-GW question being asked.

386

387 *A need for more assessment of sampling schemes* - This study has a couple notable limitations
388 that must be acknowledged in assessing the key differences between a Local Sampling and
389 Longitudinal Sampling schemes. First and foremost, both studies from the Ruhala et al. (2018)
390 data sets are snapshots in time. While they sampled at approximately the same time of year and
391 season for Local Sampling and Longitudinal Sampling schemes, they are not capturing any of
392 the potential sub-annual temporal dynamics of the biogeochemistry in the SW-GW interface. In
393 SW-GW interfaces, the biogeochemistry is typically highly variable in relation to seasonal
394 variation in nutrients, organic matter quantity and quality, and flow conditions. For example,
395 Lambert et al. (2013) found that low aromaticity DOC accumulated in the HZ in the summer and
396 was replaced in the wet season by more aromatic DOC, updating earlier research that had
397 concluded that seasonal removal of DOC was relatively stable (Findlay and Sobczak 1996).
398 Others have found that NO_3^- removal in the HZ is highly variable and dependent upon the

399 distribution of precipitation across different seasons, as precipitation controls both productivity
400 and routing of water through the HZ (Rahimi et al. 2015). In part, the biogeochemical variability
401 found in this study may be due to flow variation between the two Ruhala et al. (2018) sampling
402 periods as they observed similar biogeochemical conditions in the surface and groundwaters
403 between sampling periods. Additionally, some variability could be due to the imprecise site
404 selection from one year to the next, where the Longitudinal Sampling samples, while selected to
405 overlap with the Local Sampling sites, were not taken at the exact same locations. However,
406 given that Ruhala et al. (2018) attempted to collect at approximately the same locations both
407 years and the results from the Local Sampling indicating that variability is fairly well-
408 characterized by a single MINIPOINT at a location as compared to three MINIPOINTS at the
409 same location, we expect that the variability captured in the Longitudinal Sampling should
410 reflect the specific site from year to year.

411 This difference in flow conditions raises a second notable limitation to this study in that it is
412 a comparison between two separate years. While Ruhala et al. (2018) attempted to carry out the
413 study at similar times and seasonal conditions in each year, the hydrologic conditions were not
414 identical, nor will they ever be in most stream systems between different sampling events. In
415 many stream systems, shifts from high to low or low to high flow conditions can weaken or even
416 reverse SW-GW exchange patterns (e.g., Wroblicky et al. 1998; Boano et al. 2010) as well as
417 change the quantity and quality of solutes delivered to the SW-GW interface, such as DOC (e.g.,
418 Byrne et al. 2014; Fasching et al. 2015). Many of the limitations listed above are allayed due to
419 the well documented hydrologic stability of Augusta Creek (e.g., Poff et al. 1997). Given that the
420 majority of Augusta Creek stream water arrives in the channel through groundwater flowpaths
421 (Hamilton et al. 2018), the surface water flow fluctuations and impacts on the SW-GW exchange

422 patterns are buffered and minimized. This is to say, many of the variable flow and storm
423 response effects commonly seen in the SW-GW interface of other streams are attenuated by the
424 consistent groundwater inputs in this particular stream system and do not seem to shift the
425 overall biogeochemical conditions of the stream (Figure 8). Consequently, despite these potential
426 limitations with the data, we think that the comparison of the Local Sampling and Longitudinal
427 Sampling data sets is useful and informative for assessing how the two sampling schemes yield
428 different information, especially given that there is a paucity of network-scale SW-GW
429 biogeochemical assessments available.

430 In many cases available data do not exist or, in the case of Ruhala et al. (2018), are not ideal
431 for comparing Local Sampling and Longitudinal Sampling schemes. Therefore, in the future, if
432 there were sufficient people and equipment to conduct simultaneous sampling using both Local
433 Sampling and Longitudinal Sampling schemes, it would make for a more robust assessment of
434 the strengths and weaknesses of each sampling scheme as well as tests of our hypotheses. Still,
435 the present study results suggest that this larger investment in testing each study scheme is likely
436 warranted, because it may illustrate that different network-scale patterns of the SW-GW interface
437 biogeochemistry appear depending upon where you sample in the stream network, and inform
438 how researchers and water quality managers can expand methods to conduct SW-GW studies at
439 larger scales compatible with current watershed management plans and models (Hester and
440 Gooseff 2010; Krause et al. 2011; Harvey and Gooseff 2015).

441 **Comments and recommendations**

442 Based on the findings in this study, we recommend an increased focus on spatial
443 sampling schemes in SW-GW studies. We also found evidence in the study watershed that
444 longitudinal sampling of the SW-GW interface in favor of characterizing local heterogeneity

445 when one is interested in characterizing the SW-GW interface across a network. We must find
446 the most efficient means of sampling, because SW-GW sampling is highly demanding of both
447 labor and costs. From our initial assessment here, we determined that there was not much added
448 value (i.e., detection of biogeochemical variability) with an increased effort in the
449 characterization of local plot-scale heterogeneity (Local Sampling). There were, however, new
450 biogeochemical patterns revealed in the watershed as the sampling scheme shifted to increase the
451 number of plots sampled in longitudinal directions (Longitudinal Sampling), because it allowed
452 the same sampling effort to be distributed across more of the stream network.

453 Overall, there is a need to investigate what the best practices are for collecting SW-GW
454 interface data at watershed scales. Without data from the SW-GW interface at the scales of
455 watersheds and across river networks, it may not be possible to assess and upscale the ecological
456 function that SW-GW interfaces play in network-scale processes, such as nutrient budgets and
457 water quality management (Harvey and Gooseff 2015; Abbott et al. 2016). As highlighted here,
458 a clear, current limitation to assessing the role of SW-GW interfaces in river corridors is the
459 absence of studies of the SW-GW interface attempted at a watershed scale. Hence, a possible
460 way forward is to collect more SW-GW interface data sets at the stream network-scale from
461 different study regions and from a particular stream network across different seasons.
462 Overcoming this data gap will permit future researchers to evaluate if our findings from the
463 Augusta Creek data set are robust in terms of sampling strategy suggestions and, importantly,
464 facilitate assessments of current sampling effort utility and inspire new sampling strategies.

465 **References and Citations**

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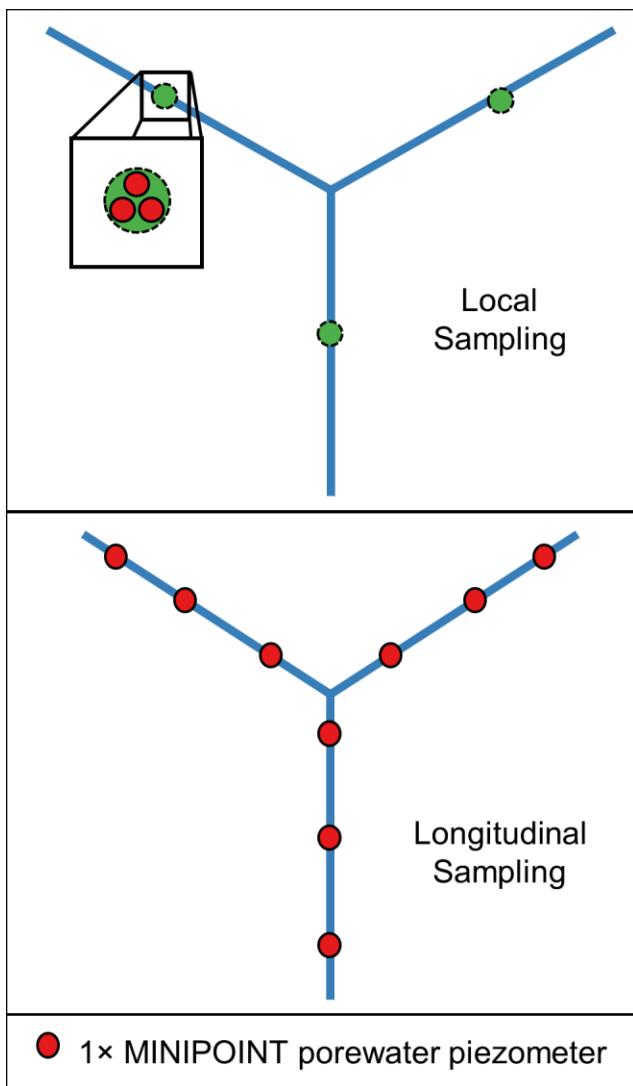
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608 **Acknowledgments**

609 Thank you to Michigan State University Department of Earth and Environmental Sciences,
610 Michigan State University Environmental Science and Policy Program, Michigan State
611 University Kellogg Biological Station Long Term Ecological Research site, and the National
612 Science Foundation Award EAR-1446328 for research support. Thank you to S. Hamilton for
613 helpful comments in developing sampling methodology and comments on this manuscript.
614 Thank you to A. Shogren for proofreading the final draft. Thank you to T. Bigg, E. Wiewiora,
615 and T. Hampton for assistance in collecting samples and to the journal editor and reviewers
616 whose constructive comments improved the paper.

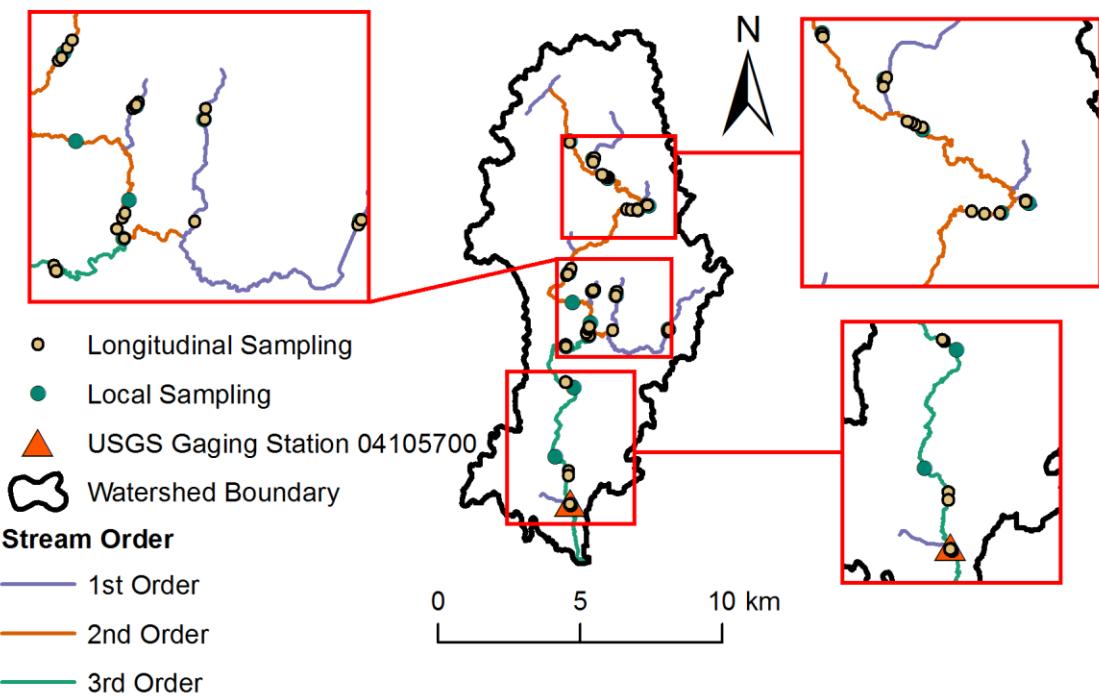
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618 **Figure Legends**



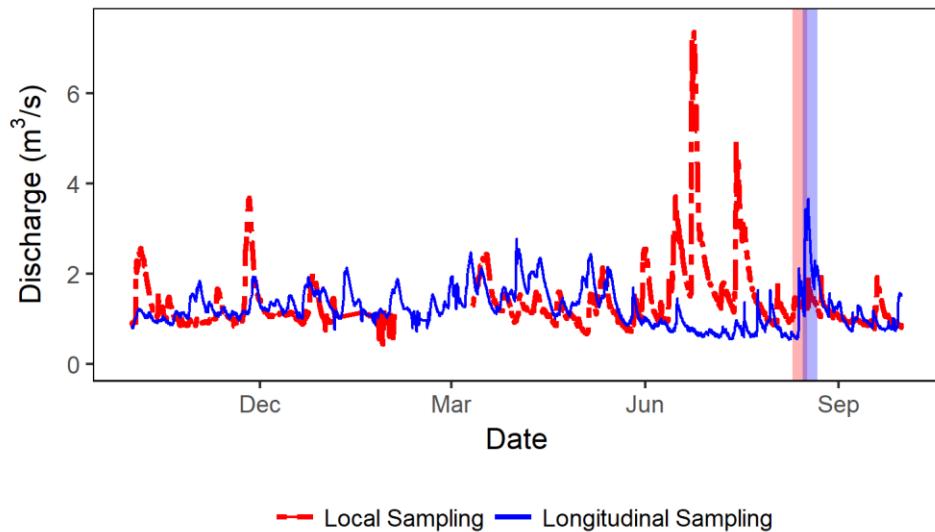
619

620 Figure 1 – Simplified plan view of stream network reaches illustrating the main conceptual
621 differences for Local Sampling (L) and Longitudinal Sampling (R) sampling schemes. Local
622 Sampling represents high characterization of local heterogeneity with low characterization of
623 longitudinal heterogeneity, while Longitudinal Sampling has low characterization of local
624 heterogeneity and high characterization of longitudinal heterogeneity. Note that each
625 MINIPOINT sample location includes up to six depths of porewater samples in the present
626 study.



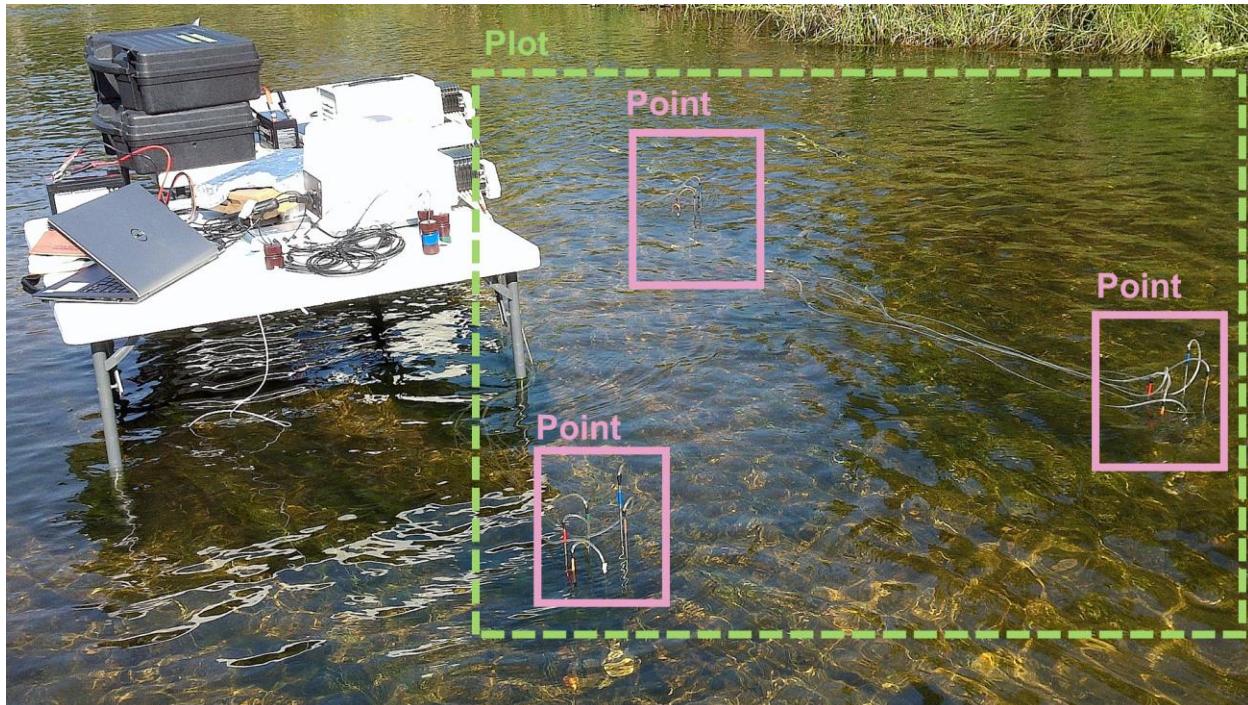
627

628 Figure 2 – Map illustrating sediment porewater sampling locations for the Local Sampling and
 629 Longitudinal Sampling campaigns, where the large, green circle symbols are the Local Sampling
 630 scheme locations, and small, yellow circle symbols are the Longitudinal Sampling scheme
 631 locations. Stream orders are identified by color, where first order streams are purple, second
 632 order streams are orange, and third order streams are green.



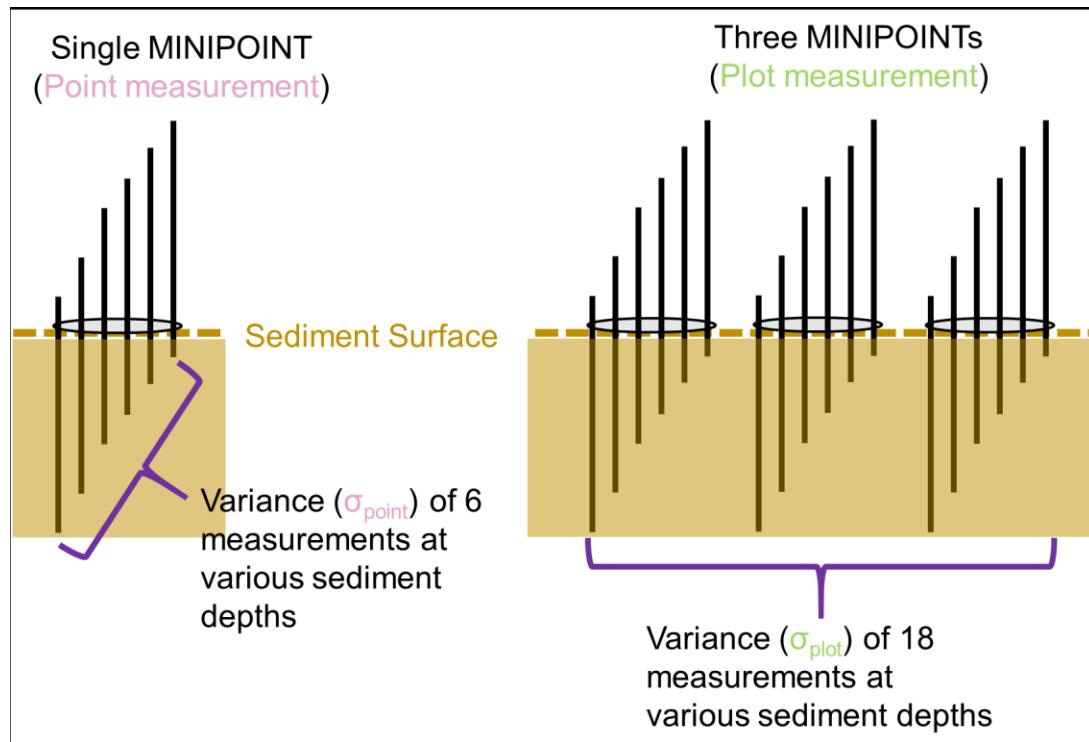
633

634 Figure 3 – Discharge conditions at the downstream USGS gaging station on Augusta Creek
 635 (04105700) for water years 2015 (red) and 2016 (blue), with shading corresponding to the Local
 636 Sampling (red) and Longitudinal Sampling (blue) efforts described in this study.

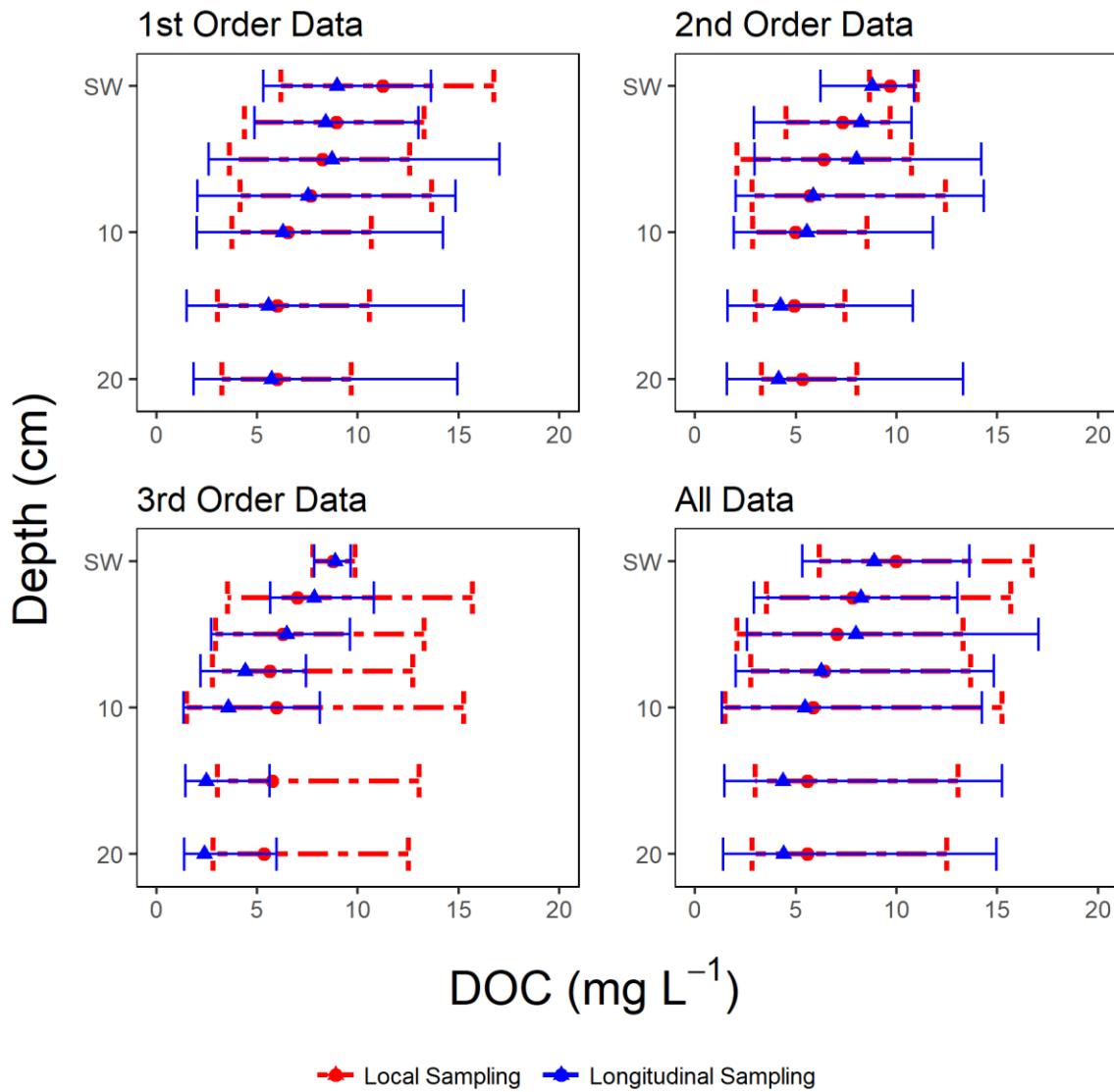


637

638 Figure 4 – Field example of the division between "points" and "plots." A point representing a
639 single MINIPOINT array at a site and a plot representing all three MINIPOINT arrays at a site
640 under Local Sampling scheme, whereas there would only be one MINIPOINT array point in a
641 plot under Longitudinal Sampling scheme.

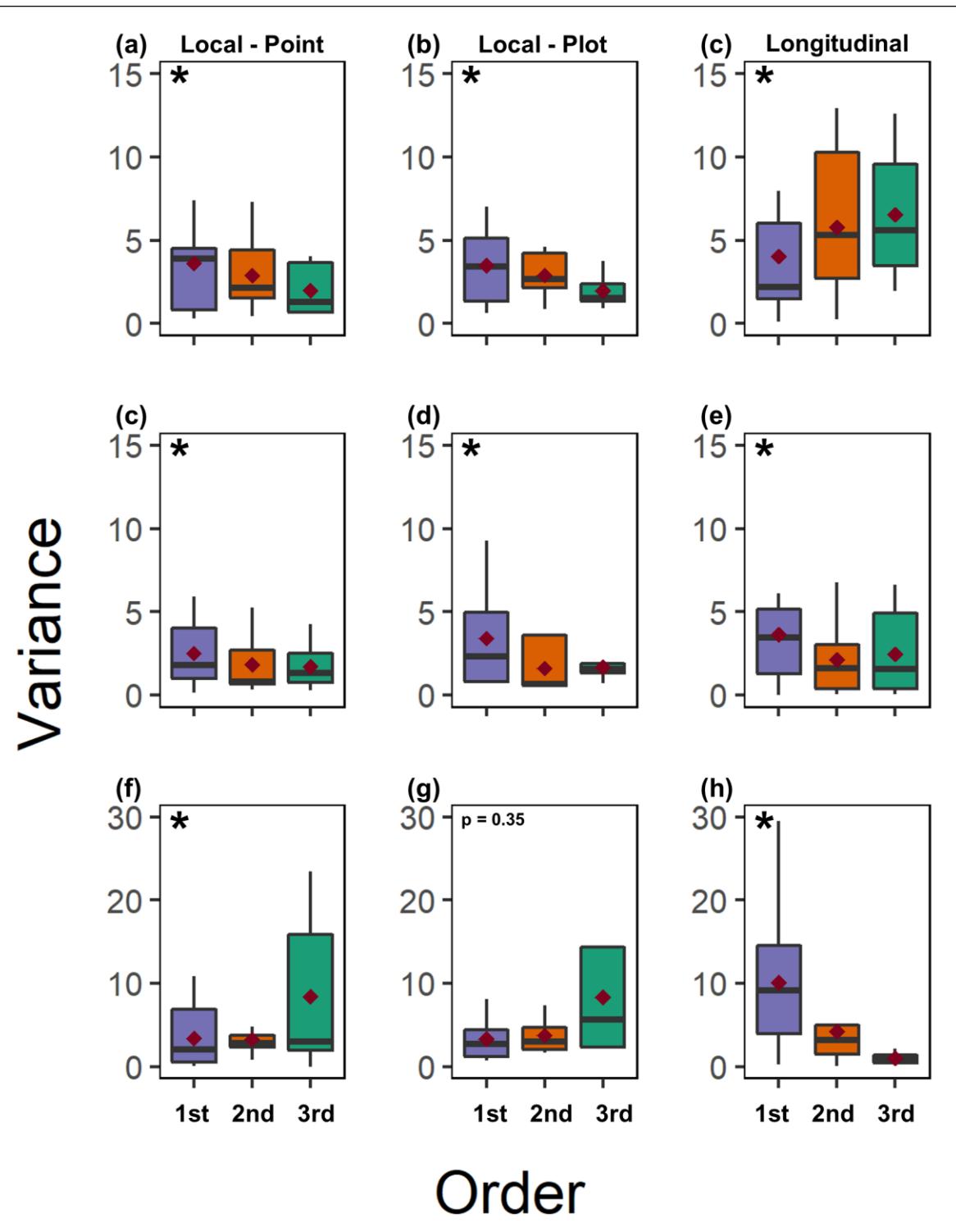


642
643 Figure 5 – Illustration of the distinction between point variance (on left) and plot variance (on
644 right) in this study. Point variance represents the variance of 6 discrete depths of a single
645 MINIPOINT, while plot variance represents the variance between all 18 measurements of the
646 three MINIPOINTS at a site.



647

648 Figure 6 – Point and whisker plots representing the mean (points) and range (whiskers) of
 649 observed porewater dissolved organic carbon (DOC) concentrations in Augusta Creek (all depths
 650 included) for both Local Sampling and Longitudinal Sampling schemes across the all of the
 651 network and grouped by stream order.

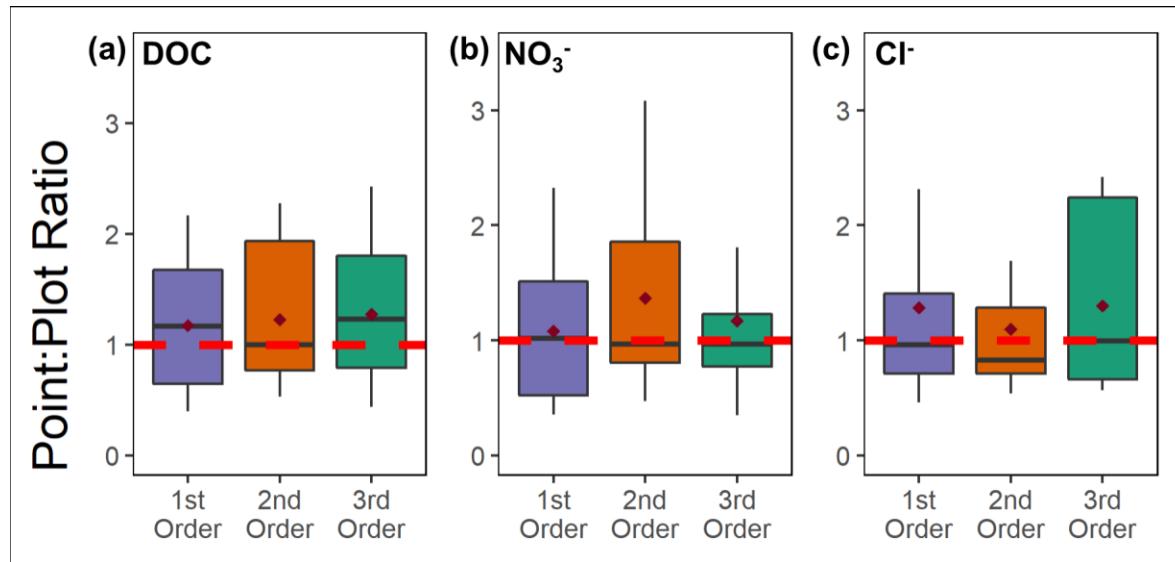


652

653 Figure 7 – Box and whisker plots illustrating the distribution of variance for Local Sampling

654 (i.e., high local characterization) and Longitudinal Sampling (i.e., low local characterization, but

655 greater longitudinal characterization) for measurements of dissolved organic carbon (DOC; a-c),
656 NO_3^- (d-f), and Cl^- (g-i) at points (a single MINIPOINT at a site) and plots (three MINIPOINTS
657 at a site) across first, second, and third-order reaches of the Augusta Creek system. Distributions
658 of the same sampling type are all significantly different per a Wilcoxon Rank Sum Test ($p <$
659 0.05), as noted with an * or otherwise stated with the specific p-value.



660

661 Figure 8 – Point (single MINIPOINT) to plot (three MINIPOINTS) variance ratios across stream
662 orders during the Local Sampling (high local characterization) sampling campaign. The box and
663 whiskers represent the quartiles at each stream order for the Local Sampling scheme, with the
664 solid line indicating median values. The red diamonds represent mean values. Ratio values less
665 than 1 indicate point variability is greater than plot variability, values greater than 1 indicate that
666 point variability is less than plot variability, and values equal to 1 indicate point variability is
667 equal to plot variability. The red dashed line represents a value of 1.